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Analysis of Object Grasping based on the Distributed Forces on the Fingertip

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ABSTRACT

In this study a dataglove is designed by installing a Force Sensing Resistor (FSR) to the thumb, index and middle fingers. The movement of fingers is involved to investigate fingertip forces produced while grasping the objects. The grasping experiments are designed by referring to the Cutkosky taxonomy in the selection of the object. The fingertip forces are analyzed to extract the grasping patterns while grasping the objects. Two grasping features are extracted, which are the Area under the Graph (AuG) and the statistical features (σ). In the experiments, the total number of 800 data sets from 5 objects is used to validate the distribution of fingertip force data and the analysis results show that it can be processed for the classification analysis. In the analysis, two classifiers are proposed, which are Linear Discriminant Analysis (LDA) and Neural Network (NN). The results show that the fingertip force data could be classified up to 94.1% and 99.4% by using LDA and NN, respectively. Both classifiers' models then are tested with fingertip force data for the purpose of the model validation and obtained the overall recognition accuracies for 5 objects of 90.0% and 96.6% by LDA and NN, respectively. The experimental results show that by focusing only on 3 fingers, which is less number of sensors, the proposed systems are capable to classify and recognize the object with the higher accuracy.

1. Introduction

Dataglove is a device used to measure the hand's location, hand's speed, hand's orientation, finger's bending while grasping an object, and recently the researchers start to install various types of tactile sensors to the dataglove. The purpose of installing tactile sensors to the dataglove is to produce a natural interaction between human and machine [1,2].

Amis [3] and Radhakrishnan [4] had proposed a cylindrical type instrument in the experiments for measuring fingertip forces produced by the fingers. The previous researchers had introduced the analysis of a static griping force and a static holding task to measure finger's forces [2]. In the studies, the FSR sensors are attached to the palmar of the fingers. Based on their finding, fingertip forces

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produced by the human hand are depending on the shapes [5] and weights of the grasped object [6, 7].

Previously, many researchers reported the recognition of object grasping by using various approaches likes utilizing of various sensors and proposing of various signal-processing techniques using the artificial intelligence approaches [8, 9]. Most of the researchers use signals from the finger's bending to recognize the object, however, in this study the methods to recognize the object are based on the fingertip forces. The experiments are designed by installing 3 units of FSR sensors to the selected fingers to capture fingertip forces when grasps the objects. The further analysis is conducted to classify and recognize the grasped objects by using the classifiers LDA and NN. Moreover, the object classification capability is discussed in details.

The outline of this research paper consists of the discussion of the related works, which is described in section 2. Section 3 describes the proposed methodologies used in the studies. Chapter 4 presents the results and discussion of the conducted experiments. Section 5 expresses the conclusions and future works.

2. Related Works

There were various types of dataglove that had been designed according to the specific tasks such as for the purpose of measuring finger's bending, force distribution and high-end dataglove, which capable to provide haptic feedback [10-12]. Dongchul Lee and Choi had published an article related to the development of wireless dataglove systems by using ZigBee wireless communication protocol [13]. The glove was attached with eight flexible bending sensors to carry out an experiment in the investigation of finger's bending to grasp the rock-paper-scissors. Another application is the development of the wheelchair systems controlled by finger's movements that had been researched and reported [14].

Besides upgrading of existing flexible bending sensor based dataglove, the researchers came out with the idea of developing the new force sensing gloves for their own use in the research [15,16]. Castro and Jr. [17] had designed and made a custom dataglove with the force sensor and the position transducer to evaluate the grasping force of drinking tasks [17]. They used the cylinder with different types of diameters and weights (but did not mentioned the exact weights). Based on the overall observations, the authors found that the largest force exerted is on thumb followed by index and the longest finger (middle) becomes a supporter for the stability of the grasping. Meanwhile, Tarchanidis and Lygouras published a research paper on how to measure the force occurs on the finger while grasping and the explanation of the theoretical calculation of the sensor also stated in the paper [18]. The session of collecting force data has been conducted by instructing the human subjects to wear the dataglove with the installation of the force sensor to carry out the pick ball task.

Palm and Iliev [19] had developed the framework of grasping activities with 15 different objects. The objective of the research is to recognize the grasping type by robotic arm with the guidance of the dataglove wearer. The grasping task had been conducted by using CyberGlove as a tool. A takagi-Sugeno fuzzy model is used to model the individual grasp's type with the time instant as an input and finger joint angle as the outputs. A time clustering, fuzzy modelling and Hidden Markov Model (HMM) are used by the authors to compare the recognition accuracy obtained when process the information of the hand. The final results show that the overall recognition accuracy obtained is above 60% for all classifiers. The highest recognition accuracy is obtained by using fuzzy-modelling, which is 68.6%. Meanwhile, the second and third highest recognition accuracies are 66.5% for time-clustering classifier and HMM obtained 66.3%.

Dai, Sun and Qian [20] published a paper, which presents a novel grasping motion analysis technique based on a functional Principal Component Analysis (fPCA). The experiments are conducted by using 5DT dataglove 14 ultra to record 14 joints of the fingers. Nine objects are selected to accomplish 15 different types of grasp according to the Cutkosky taxonomy. Five human subjects performed the grasping task. Based on the results obtained from fPCA analysis, the overall recognition accuracy is 97.24%.

In this research, the low cost FSR sensors are attached to the fingertip of the thumb, middle and index fingers. The proposed fingertip force features and classifiers are able to classify five different objects with the accuracies 94.1% and 99.1%, respectively. On the other hands, by reducing the number of sensors, the proposed methods are capable to classify and recognize the objects with higher accuracy.

3. Methodologies

3.1 The Flow of the Methodologies

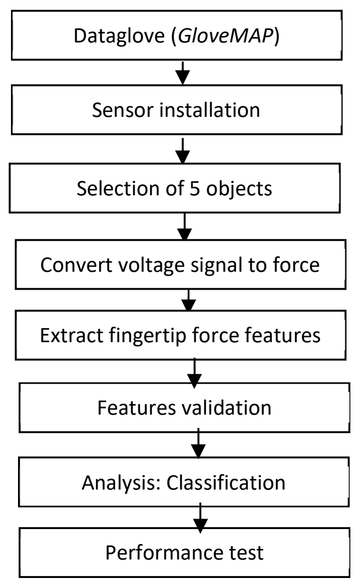


Fig. 1. The flow of the methodologies

The handmade dataglove called GloveMAP was used in the experiments. The FSR sensors were installed to the palmar of the selected fingers of the dataglove. The voltage divider concept was employed to acquire fingertip force signals, Vout. Five objects were chosen in the experiments and the object selection criteria were based on the Cutkosky taxonomy. The signal processing approaches were employed to analyze the collected finger forces data from the experiments. The performance of the proposed system was evaluated by using data classification approaches. The flow of the proposed research methodologies is shown in Figure 1.

3.2 Collecting Finfertip Force Signals

The electronic circuit was designed to collect voltage signals outputted from the FSR sensor's terminal. Let's connects two electrical impedances Z1 and Z2 in series as shown in Figure 2. The relationship between the input voltage, Vin and the output voltage, Vout can be found by applying voltage divider theorem as shown in (1). In the actual GloveMAP configuration, Z1 was replaced with a FSR sensor and Z2 was 10 kΩ resistor [21]. Figure 3 shows the voltage signals outputted from Vout. The results show the signals outputted from Vout when the subject grasps the object for 3 s.

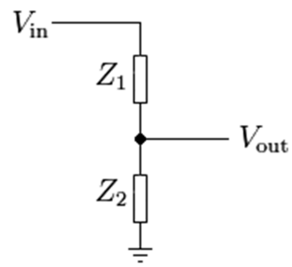


Fig. 2. A circuit of output force signals, V_{out}

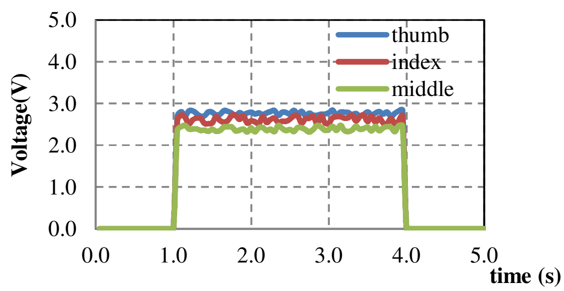


Fig. 3. The output voltage signal from V_{out}

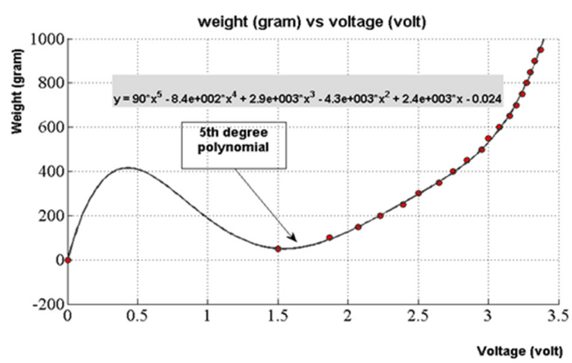


Fig. 4. The weight and voltage relation based on 5th degree polynomial

$$V_{out} = V_{in} \cdot \frac{Z_2}{(Z_1 + Z_2)} \tag{1}$$

3.3 Transformation of Voltage Signals into Force Signals

The FSR terminals outputs the voltage values ranging from 0 to 5 V. For the purpose to understanding the concept of the force applied on the fingertip, the voltage signal was converted to the force signal. The transformation between voltage and force on the fingertip need be investigated to find the best fix of the correlation. In order to do the transformation, a polynomial regression technique was proposed in the studies [21]. The voltage outputted from the circuit Vo was used as an input to the fifth degree polynomial equation as shown in (2) to determine the related mass, g. The mass, g was then used in order to convert the output voltage signal into the force signal as shown in Figure 4. The variable x was the voltage value obtained from the experiments.

$$g = 90x^5 + 8.4e^2x^4 + 2.9e^3\,x^3 - 4.3e^3\,x^2 + 2.4e^3\,x - 0.024 \quad (2)$$

3.4 Fingertip Force Features

3.4.1 The area under the graph (AuG) as the fingertip force feature

The length, *l* as mentioned in (3) was the amplitude of the fingertip force signal as shown in Figure 5. The round line labeled in the graph shows the amplitude of the signals. The width, *w* as mentioned in (3) was the interval between the rising edges of two signals. Both *l* and *w* were used to calculate the *AuG* of the fingertip force signals [20].

$$AuG = l \times w \quad (3)$$

l = amplitude of the fingertip force signal,
w = interval between the rising edges of the fingertip force signal.

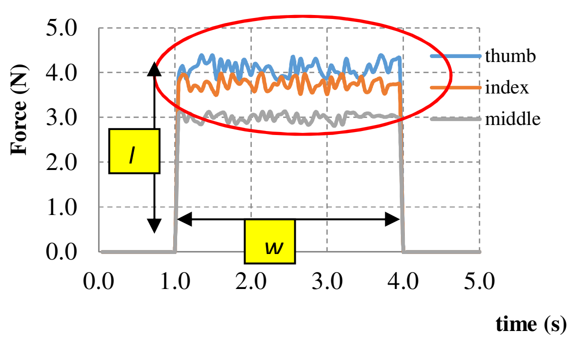


Fig.5. Fingertip force signals of the object cylinder

3.4.2 Standard deviation, σ as the fingertip force feature

Based on the previous studies [21], the statistical feature, which was a standard derivation, σ was significant as a feature to represent fingertip forces data. The distribution of its value provides the insight of how data was scattered or dispersed.

$$\text{Standard deviation } (\sigma) = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - \mu)^2} \quad (4)$$

$$\mu = \frac{1}{n}\sum_{i=1}^{n} x_i \quad (5)$$

x_i = the fingertip force data
μ = the mean value of the fingertip force data
n= the number of the fingertip force data

3.5 Fingertip Forces Features Validation

The distribution of the selected fingertip force was validated to monitor the fitness, accuracy and consistency. Statistical analysis software was used in order to validate the reliability of the proposed features. In the analysis, data from several groups of the extracted fingertip force features were tested in term of a common mean and to determine whether the measured characteristics were different for each group. The groups are referred to the 5 selected objects. The procedures below were used in order to determine the *P*-value at the end of the analysis.

3.5.1 Mean value within the similar group and in 5 different groups of objects

$$\mu_i = \frac{\sum X_i}{n_i} \tag{6}$$

$$\mu_T = \frac{\sum X_1 + X_2 + X_3 + X_4 + X_5}{n_T} \tag{7}$$

μ_i = the measured mean value of the similar object
μ_T = mean of 5 groups of objects
i = {1,2,3,4,5}
n_T = Total fingertip force data of 5 of objects

3.5.2 Sum of Square within group and between groups of the objects

The sum of squares represents the variation of fingertip force data within group and between groups of the fingertip force data.

$$S_G = (X_1-\mu_1)^2+(X_2-\mu_2)^2 +\ldots+ (X_5-\mu_5)^2 \tag{8}$$

$$S_{BG} = (X_1-\mu_T)^2 + (X_2-\mu_T)^2 +\ldots+ (X_5-\mu_T)^2 \tag{9}$$

$$S_{TG} = S_G + S_{BG} \tag{10}$$

S_G = the sum of square (within the group)
S_{BG} = the sum of square (between groups)
S_{TG} = the sum of square (All groups)
μ_i = the measured mean value of the similar object
μ_T = the mean of all groups
X_i = data of each group
i = {1,2,3,4,5}

3.5.3 Degree of Freedom (DOF) within group (DOFG) and between groups (DOFBG) of the objects

DOF is a degree of freedom in a system where the number of parameters of the system may vary independently.

$$DOF_G=n-i \tag{11}$$
$$DOF_{BG}=i-1 \tag{12}$$

n = total quantity data / number of data
i = {1,2,3,4,5}

3.5.4 Mean square within group (MS_W) and between groups (MS_B) of the objects

The mean square refers to an estimated population variance based on the variability among a given set of measures. It is measured by dividing the corresponding sum of squares by the DOF.

$$MS_G = S_G \div DOF_G \quad (13)$$
$$MS_{BG} = S_{BG} \div DOF_{BG} \quad (14)$$

The *F*-ratio is determined by dividing the mean square value of between groups (MS_{BG}) variations with the mean square value of within group (MS_G) variation. On the other hands, the *F*-ratio represents a measure of how different the means are relative to the variability within each sample.

$$F = MS_G \div MS_{BG} \quad (15)$$

3.6 Linear Discriminant Analysis (LDA) for Classification of the Objects

LDA is a supervised learning classification method to classify observation into two or more groups, which are relies on the selected features AuG and σ. In this study, LDA was used to classify 5 selected objects, which were planar (plywood), cylinder (can), rectangular (box), spherical (ball) and disc (CD). The total of 800 data sets or 160 data sets from each object were used to model LDA in the training phase. A Linear Discriminant Function and a Linear Discriminant Coefficient were computed in the classification process. The algorithms below were applied to do the classification of 5 selected objects.

$$f_i = \mu_i C^{-1} x_k^T - \frac{1}{2}\mu_i C^{-1} \mu_i^T + \ln(p_i) \quad (16)$$

Where;
f_i = the group of the object
x_k^T = the object transpose of the row *k*
μ_i = the mean of observation in a similar group of the object
C^{-1} = the inverse covariance matrix
μ_i^T = the mean transpose of observation in a similar group of the object
p_i = the prior probability vector
i = {1,2,3,4,5}

Meanwhile, to calculate the pooled covariance matrix is as provided in (17).

$$C(r,s) = \frac{1}{N}\sum_{i=1}^{g} n_i . c_i(r,s) \quad (17)$$

where,
$$c_i = \frac{(x_i^o)^T x_i^o}{n_i}$$
$$x_i^o = x_i - \mu$$
x_i = the observation of object in group *i*
μ = the global mean vector

n_i = the number of observation in a similar group of the object
(r, s) = the row and column of matrix
g = the covariance matrix group
N = the total number of observation
i = {1,2,3,4,5}

3.7 Neural Network (NN)

Neural network classifier is also known as Artificial Neural Network (ANN). It is been call as an artificial system due to the neuron cell made up for the system by imitating how the human brain's neuron works. The concept of the NN classifier is the interconnection pattern between the different layers of neurons. Neuron consists of input unit, output unit and hidden unit used in the training process with the involvement of features data. Figure 6 shows the process involved in Neural Network training for the classification.

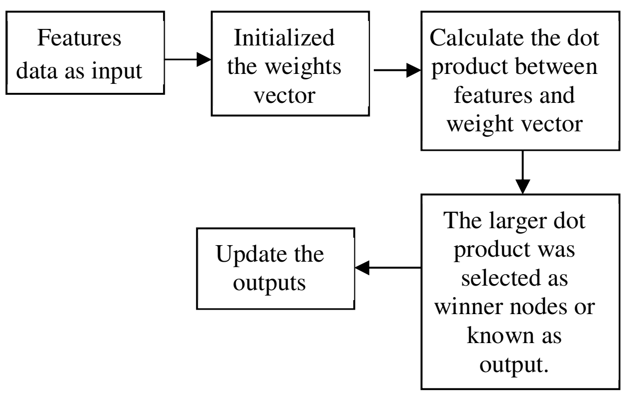


Fig.6. The flow process of Neural Network

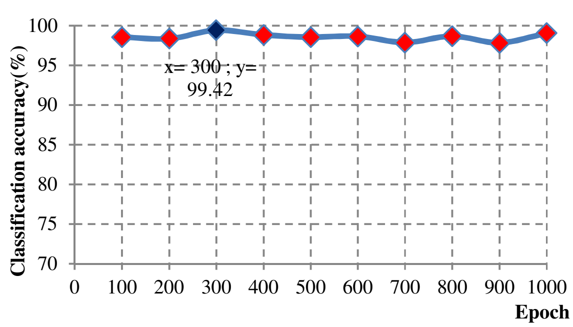


Fig.7. The classification accuracy versus training epochs

The number of epoch had been tested from 100 to 1000 in the system. The best classification performance was shown at number of epoch equals to 300, which gave the highest classification and recognition accuracies compared to the others. The experimental results are shown in Figure 7.

4. Results and Discussion

4.1 Experimental Setup

In the experiments, 20 subjects were participated to collect the fingertip force's information. The subjects were asked to grasp the objects for about 3 to 4 s. The tasks were repeated for 10 trials for each subject and object. Thus, a total of 1000 sample fingertip force data were collected. The glove was set up as shown in Figure 8 and the selected objects as shown in Figure 9. The object selection criteria were based on the Cutkosky taxonomy.

Fig.8. GloveMAP

Fig.9. Objects selected

4.2 Experimental Results
4.2.1 Grasping features

There are 5 different shapes of object have been used to collect force's information exerted on thumb, index and middle fingers. The planar (plywood), cylinder (can), rectangular (box), spherical (ball) and disc (CD) are chosen in the experiments. Due to the finding in the preliminary experiments, which is the weight of the object that affects the grasping force, the object's weights are decided to be 200 g approximately. The fingertip force data obtained from the grasping activities are plotted as shown in Figure 10 and 11.

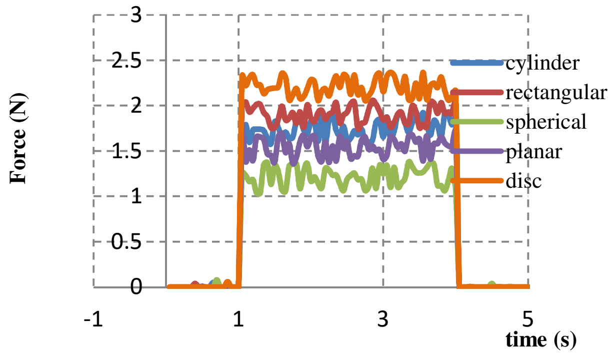


Fig.10. Forces exerted on thumb when grasping 5 objects

The disc had the highest grasping force for the thumb compared with the other objects, follows by the rectangular and the cylinder. The Spherical has the highest grasping force for the index compared with other objects, follows by the disc and the rectangular. The results indicate each finger contributes different distribution of forces when grabs different objects.

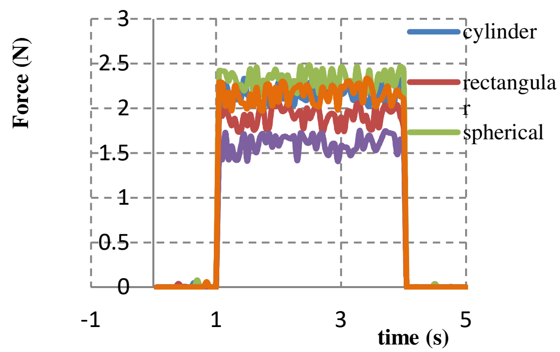


Fig.11. Force exerted on index finger when grasping 5 objects

Table 1
Area under the graph for thumb finger

Subjects	Cylinder	Rectangular	Spherical	Planar	Disc
#1	6.280	6.003	7.272	4.853	6.778
#2	6.860	5.659	7.432	4.867	6.572
#3	6.613	5.888	6.751	5.154	6.164
#4	6.240	6.065	7.280	4.641	6.094
#5	6.285	5.916	6.484	5.075	6.072
#6	6.954	5.214	7.326	5.151	6.693
#7	6.534	5.486	6.763	4.599	6.447
#8	6.870	5.745	6.761	4.424	6.236
#9	6.940	5.827	7.321	4.787	6.754
#10	6.732	5.750	6.968	4.801	6.635

Table 2
Area under the graph for thumb finger

Subjects	Cylinder	Rectangular	Spherical	Planar	Disc
#1	5.039	5.241	3.552	4.324	6.359
#2	5.229	5.417	3.568	4.858	6.598
#3	4.784	5.463	3.190	4.967	6.166
#4	4.794	5.883	3.323	4.551	6.333
#5	4.853	6.172	3.936	4.669	6.540
#6	5.455	6.048	3.259	4.510	6.964
#7	5.529	5.809	4.040	4.546	7.059
#8	4.962	5.529	3.740	4.222	6.463
#9	5.626	5.614	4.028	4.360	6.972
#10	4.917	5.286	3.296	4.968	7.102

Table 3
Area under the graph for middle finger

Subjects	Cylinder	Rectangular	Spherical	Planar	Disc
#1	4.832	2.201	6.890	3.145	6.085
#2	4.915	2.469	6.852	3.358	5.901
#3	4.405	2.365	6.083	3.683	6.102
#4	4.631	2.403	6.086	3.160	5.919
#5	4.886	2.249	6.119	3.995	5.743
#6	4.988	2.403	6.967	3.684	5.702
#7	4.170	2.204	6.490	4.134	5.594
#8	4.935	2.207	6.916	3.636	6.115
#9	4.179	2.266	6.340	3.160	6.098
#10	4.651	2.186	5.996	3.918	6.187

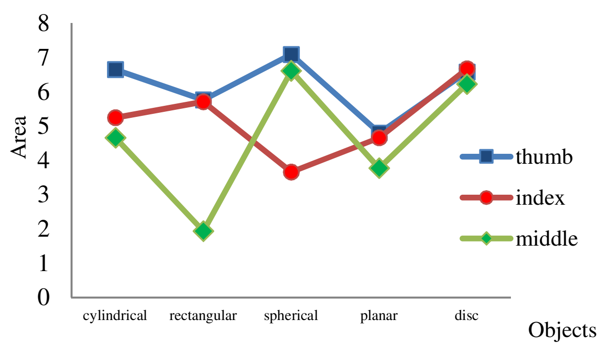


Fig. 12. The area under the graph for all objects

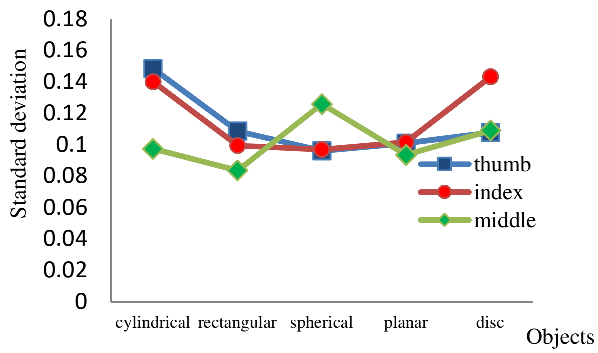


Fig. 13. σ for all objects

Table 1, 2 and 3 show the collected data for the area under the graph of the thumb, index and middle fingers for 10 subject. Meanwhile, Figures 12 and 13 show the distribution data for the area under graph and σ of all fingers and the related objects. The plotted graphs are the average values of the area under graph and σ measured from the experiments.

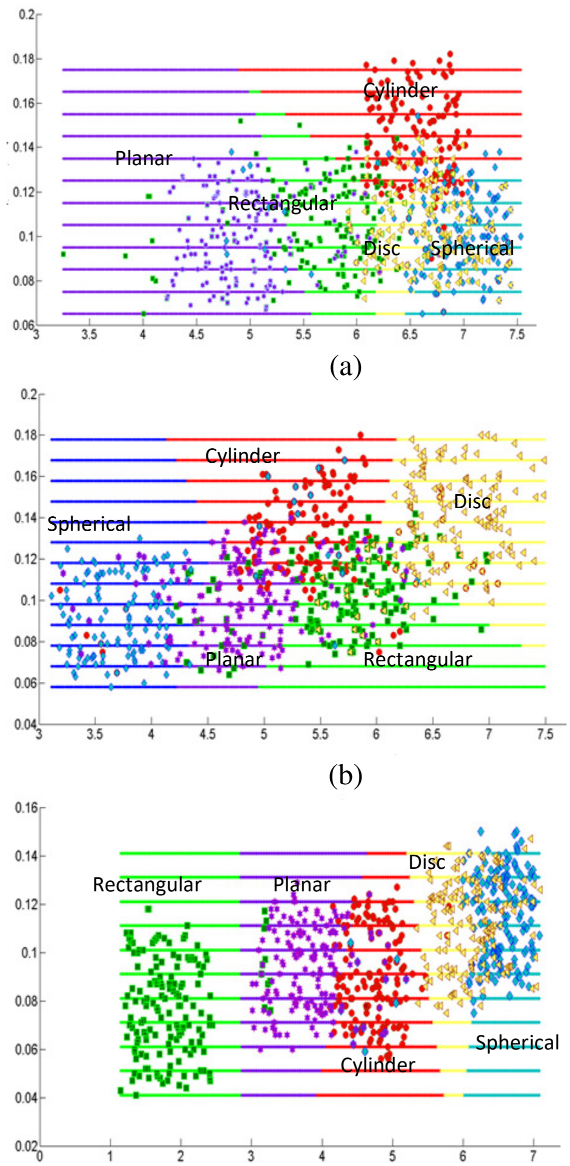
4.2.2 Features validation

The total number of 800 data sets from all features is used to do data validation using statistical software ANOVA. As can be seen, the *P*-value of three fingers indicated that *P* is equal to 0 (P=0), which is less than 0.05 (P<0.05). The sum of square represents the variation of data between groups and data within group. The data distribution between the groups contributed much higher value than within group, which give the meaning of the means value for all objects are not the same. Based on this finding, the selected fingertip force's features are different to each other for all fingers**.**

4.2.3 Classification and Recognition

In overall, data have been separated randomly for 80% to 20% for the training and testing, respectively. On the other hands, each object contributed 160 data to be trained in the classification process and 40 data to be used in recognition process that give a total of 800 and 200 of data, respectively.

Figure 14 shows the performance of LDA classifies the selected 5 objects based on the fingers as numbered by (a), (b) and (c), which represent by thumb, index and middle fingers respectively. The colored purple, green, red, yellow and blue data represent the objects planar (plywood), rectangular (box), cylinder (can), disc (CD) and spherical (ball). Figure 14 (a) and (c) show that the distribution of the fingertip forces for the thumb and middle fingers mix or redundant for the object disc (CD) and spherical (ball). The results show that almost similar distribution of the fingertip forces is exerted on the thumb and middle fingers when grasping the disc (CD) and spherical (ball), however, is separately classified for the rest of the objects. Figure 14 (a) and (c) also show that the distribution of the fingertip forces for the thumb and middle fingers for the object rectangular (box) and planar (plywood) had a similar pattern because they are placed close to each other. Moreover, based on the appearance of the LDA output could be concluded that the capability of the proposed fingertip's features to classify the objects.



(c)

Fig. 14. LDA classification performance: (a) Thumb (b) Index (c) Middle

Tables 4 shows the numerical analyses of the classification and recognition results. The results could be used to support the classification capability of the proposed fingertip's features as discussed based on the results as shown in figure 14. The overall classification rates obtained by LDA and NN are 94.13% and 99.42%, respectively. The highest classification rates acquired by LDA and NN classifiers belong to the disc and planar objects. Moreover, the lowest classification rate was spherical (ball) for both classifier LDA and NN. Meanwhile, Table 5 shows the recognition results. The overall recognition accuracies acquired by LDA and NN were 90.00% and 96.59%, respectively. Tables 6 and 7 show the results of the confusion matrix for both LDA and NN. Similar to the classification results, the recognition accuracy for the object spherical (ball) was the lowest.

Table 4
LDA classification rates

Object	Linear Discriminant Analysis (LDA)	Neural Network (NN)
Cylinder	95.0 %	99.3%
Rectangular	93.8 %	99.6%
Spherical	85.6 %	98.2%
Planar	97.5 %	100%
Disc	98.8%	100%
Total rate	94.1 %	99.4%

Table 5
Recognition accuracies

Object	Linear Discriminant Analysis (LDA)	Neural Network (NN)
Cylinder	87.5 %	96.4%
Rectangular	90.0 %	92.4%
Spherical	85.0 %	96.0%
Planar	92.5 %	98.8%
Disc	95.0 %	99.4%
Total rate	90.0 %	96.6%

Table 6
Confusion matrix for LDA classifier

Object	Classification confusion matrix					Accuracy (%)
	Cylinder	Rectangular	Spherical	Planar	Disc	
Cylinder	151	0	4	1	4	94.4
Rectangular	0	150	0	10	0	93.8
Spherical	12	0	**137**	0	**11**	85.6
Planar	4	0	0	156	0	97.5
Disc	2	0	0	0	158	98.8
			Total %			94.0

Table 7
Confusion matrix for NN classifier

Object	Recognition confusion matrix					Accuracy (%)
	Cylinder	Rectangular	Spherical	Planar	Disc	
Cylinder	35	0	5	0	0	87.5
Rectangular	1	36	0	3	0	90.0
Spherical	6	0	34	0	0	85.0
Planar	1	0	0	37	2	92.5
Disc	0	0	2	0	38	95.0
			Total %			90.0

4. Conclusion

The main goal of this research was to analyze the object's grasping based on the distribution of forces produced by the human's fingertip. A low cost FSR sensor is used and installed to the thumb, middle and index fingers. The fingertip grasping signals are acquired and analyzed. The experiments are designed based on the grasping type of Cutkosky taxonomy. The grasping signal patterns are investigated, and the best features were selected to be used in the classification and recognition processes. The proposed classifiers are capable to classify 5 selected objects with the classification rates of 94.13% and 99.42% for LDA and NN, respectively. Besides, the recognition accuracies achieved from the both classifiers were 94.0% and 90% for LDA and NN, respectively. The proposed systems recognize the objects (cylinder, rectangular, spherical, planar and disc) with high accuracies, which the average more than 90%. Moreover, the proposed 3 fingers which are thumb, middle and index and the selected fingertip force's features are the significant variables to be used in the development of the computational systems for recognizing object based on the fingertip's force. The advantage of the studies is by reducing the number of sensor, the systems could classify and recognize the objects identified from the group in Cutkosky taxonomy. In the future, to increase the classification rate and the recognition accuracies, individualities could be investigated, and the weighting approaches could be proposed to consider the contribution of the individual finger.

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